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# COMPUTATIONAL MODELING OF VISUAL PERCEPTION AND ITS APPLICATION TO IMAGE ENHANCEMENT

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## ABSTRACT

As digital cameras have become ubiquitous, most images we see now are digital. However, digital imaging is not based on human visual perception. Here, we propose computational models of lateral inhibition and light/dark adaptation, which are characteristics of human vision, and of color perception. A combined model relates human visual characteristics to human perception. We used this model to enhance images and to overcome defects in color vision. Our approach generated easily viewable images which create unchanged impressions in viewers.

***Keywords:*** *visual characteristic, lateral inhibition, light/dark adaptation, image enhancement, defect in color vision*

## 1. INTRODUCTION

As digital cameras have become ubiquitous, most images we see now are digital. However, these images might convey different impressions from the original circumstances because of characteristics of the human visual system such as lateral inhibition. For this reason, it is necessary to develop technologies which make digital images easier to see while maintaining the original impressions of the images. Human senses are measured by changing the sense

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inputs while testing whether subjects can perceive such changes in psychological terms [1]. In this context, impressions mean perceptions of brightness and color [2]. The impressions are highly correlated with the composition, which consists of the overall brightness of an image, the color tones, and the texture (color differences) [3][4].

Images can be retouched in image processing software. However, the impressions of the images may be altered radically from those of the original images, depending on the retouching algorithms. For example, histogram equalization [5] increases the visibility of images, but also changes impressions. Here we propose a method of increasing the visibility of an image while retaining the impressions evoked by the original image. Here, visibility indicates that the viewer can comprehend the content of the image.

Many conventional image processing algorithms are based on statistical characteristics, such as the components of brightness and the distribution of color differences, and ignore local image characteristics. For example, histogram equalization, which is generally used to enhance images, enhances the values of image characteristics based on statistical quantities, but lacking a relationship with the human visual perception system, it often alters the impressions of the original images [6].

Here we developed a mathematical model of the elements of brightness and color based on the mechanisms of the receptive fields by focusing on the mechanism of lateral inhibition, which is one of the visual characteristics of humans. Using the model, we propose a method of correcting images to make them easily perceptible to viewers without altering the viewers' impressions.

## 2. MATHEMATICAL MODEL OF VISUAL CHARACTERISTICS

The algorithm we propose is designed to improve the visibility of an image by correcting the elements of brightness and color differences while keeping the impressions of the original images unchanged. It is based on the mechanism of lateral inhibition, a visual characteristic of humans, and on the characteristics of the response to light stimulus.

### 2.1. Characteristics of response to light stimulus

Humans sense light through horizontal cells located on the retina. The horizontal cells are nerve cells which form synaptic connections with the visual cells [7][8]. The response to light stimulus shows an S-shaped curve (Fig. 1) [9]. This curve indicates that the visual acuity of humans declines at the extremes of brightness and darkness. It is important to compensate for these restrictions without impairing the impressions of images because of the need to cater to the sensitivity of viewers to the visibility of the images.

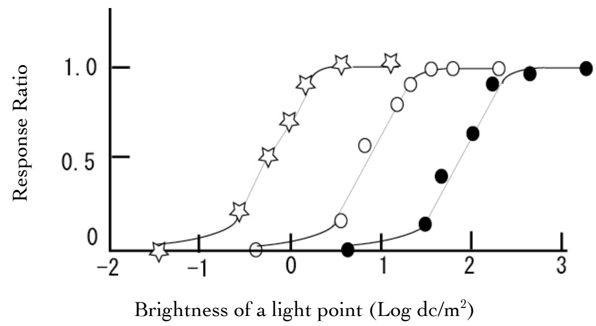



**Figure 1:** S-curve response characteristics of horizontal cells [9]

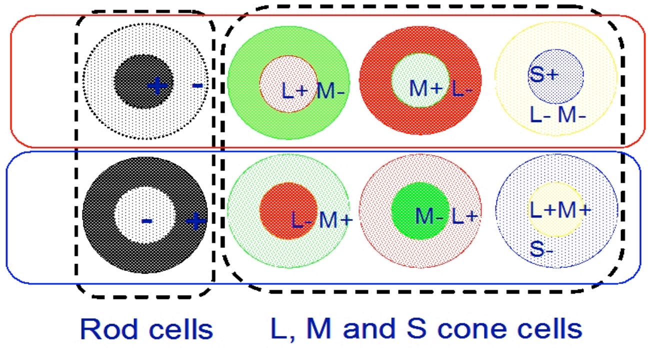



**Figure 2:** Mechanisms of receptive fields.

### 2.2. Lateral inhibition

In lateral inhibition, amacrine cells in the eye suppress surrounding cells when the nerve cells trigger an excitatory action after receiving light, thus enhancing brightness contrast and color contrast [8]. Well-known examples of antagonism to colored light by the optic nerves in the visual receptor include the mechanisms of the brightness and color contrast-based receptive fields (Fig. 2) [10].

#### 2.2.1. Lateral inhibition for brightness elements

The brightness contrast-based receptive field is described by 2 models: the On-Center model, in which a phasing signal is reversed against stimulus from the retinal rod, and the opposite Off-Center model. In the On-Center model, the surrounding light triggers an inhibitory action when light at a certain point causes an excitatory action. The Off-Center model is the opposite.

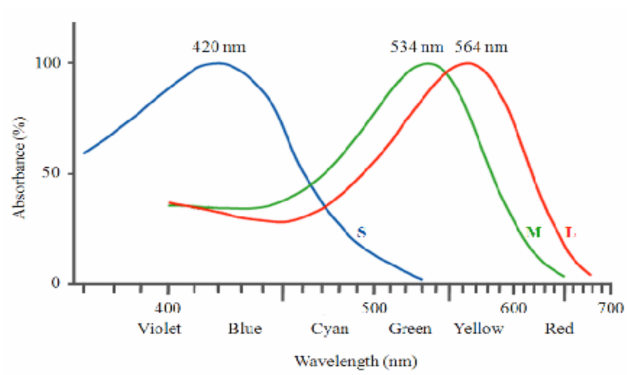



**Figure 3:** Cones' response to wavelength[13]

2.2.2. Lateral inhibition for color difference elements

The color contrast-based receptive field triggers lateral inhibition upon stimulus from 3 cones, the L, M, and S cones. The cones are visual cells which respond to bright spots and are capable of discerning colors (Fig. 3). The L cone can discern long wavelengths (red: R), the M cone can discern medium wavelengths (green: G), and the S cone can discern short wavelengths (blue: B). The response to stimuli from these 3 cones gives 4 receptive fields:

- R-centered – G-surrounding (On-Center & Off-Center)
- G-centered – R-surrounding (On-Center & Off-Center)

For example, in the G-centered – R-surrounding (On-Center) model, once a green light at a certain point causes an excitatory action, the surrounding red light triggers an inhibitory action. As the number of cells in the S cone and L+M cones (yellow: Y) is smaller than that of R and G, On-Center and Off-Center have only one model of receptive field each (there is no Center, and B and Y inhibit each other), as shown in Fig. 2, and have weaker color contrast than R and G.

Thus, the receptive fields are assumed to detect and enhance local contrasts in brightness and color phase, as their actions are based on the relationship of the light stimulus at a certain point and its surroundings. Such a mechanism corrects colors, as the colors look stronger or weaker than the actual color differences.

## 3. MATHEMATICAL MODEL OF VISUAL CHARACTERISTICS

We simulated the mechanisms of the receptive fields and developed a mathematical model of the lateral inhibition by using the following procedures:

### 3.1. Converting RGB values into V, $C_{R-G}$, $C_{Y-B}$ values

To develop brightness and color contrast-based models, we converted RGB values into brightness elements and color difference elements. Brightness is represented by V, and the color difference is represented by $C_{R-G}$ (contrast between R and G) and $C_{Y-B}$ (contrast between Y and B).

$$V = \frac{1}{3}R + \frac{1}{3}G + \frac{1}{3}B \qquad (1a)$$

$$C_{R-G} = \frac{1}{2}R - \frac{1}{2}G \qquad (1b)$$

$$C_{Y-B} = \frac{1}{4}R + \frac{1}{4}G - \frac{1}{2}B \qquad (1c)$$

### 3.2. Brightness contrast model based on reverse S-curve

The brightness contrast model (the "V circuit") replaces original images with positive images (On-Center model) or negative images (Off-Center model). The combination of positive and negative elements makes brightness contrast recognizable to viewers.

The intensity of each pixel of an image in which the contrast is enhanced is expressed by both:

- the intensity of the positive image: a value relative to the minimum value of the intensity of an input image
- the intensity of the negative image: a value relative to the maximum value of the intensity of an input image.

The linear sum of both values is obtained as follows [6][11]:

$$dV_{pos} \propto \frac{dV}{V - V_L} \qquad (2a)$$

$$dV_{neg} \propto \frac{dV}{V_U - V} \qquad (3a)$$

The Weber–Fechner Law [12] (the difference in intensity that humans can sense is proportionate to the logarithm of the intensity) was applied to Eqs. 2a and 3a to obtain Eqs. 2b and 3b:

$$dV_{pos} \propto -\log(V_U - V) \qquad (2b)$$

$$dV_{neg} \propto \log(V - V_L) \qquad (3b)$$

where VL and VU represent the minimum and maximum values in the dynamic range of input. The intensity was converted based on the linear sum of the positive and negative images as:

$$dV \propto dV_{pos} + dV_{neg} \qquad (4a)$$

The formula after assigning Eqs. 2a and 3a becomes:

$$dV \propto \frac{dV}{V - V_L} + \frac{dV}{V_U - V} \qquad (4b)$$

Taking Eqs. 2b and 3b into consideration gives Eqs. 4a and 4b:

$$V \propto V_{pos} + V_{neg} \qquad (5a)$$
$$\propto \log(V - V_L) - \log(V_U - V) \qquad (5b)$$

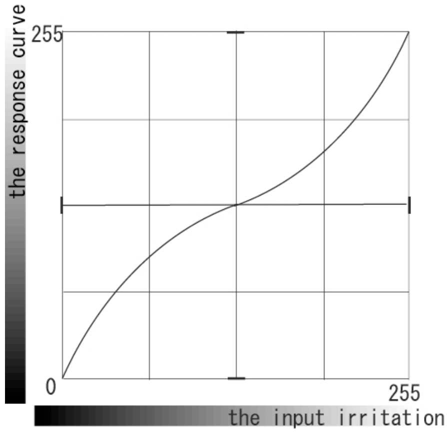



**Figure 4:** Example of reverse S-curve of brightness contrast.

The V circuit model enhances the contrast and sharpness of the brightness by employing a function which is represented by a reverse S-curve (Fig. 4) to compensate for the decline in human visual acuity in bright and dark areas. Therefore, the brightness contrast model can be defined as:

$$V(v) = \log \frac{v - V_L + \delta_{pos}}{V_U - v + \delta_{neg}} \qquad (6)$$

where v represents a value entered, V(v) represents a corrected value, and $\delta_{pos}$ and $\delta_{neg}$ represent constants of integration.

The proposed method changes the values of constants of integration described as $\delta_{pos}$ and $\delta_{neg}$ in Eq. 6 by taking into consideration the characteristics of the entire image and local characteristics, for the following reasons:

- The S-shaped response characteristics of the horizontal cells show that vision declines in bright and dark areas, of which many images have both at the same time.
- Considering overall characteristics only may create images with locally unnatural characteristics.
- Correcting images by considering only local characteristics may radically alter the impressions of the images.

For these reasons, it is necessary to consider both local and overall characteristics in the constants of integration.

Therefore, the formulae become:

$$\delta_{pos}(V) = \alpha_{pos}(V_u - V) \times \frac{((V_{gmean} - V_L) + c_{pos}(V_{lmean} - V_{l\min}))}{((V_U - V_L) + c_{pos}(V_{l\max} - V_{l\min}) + l_{pos})} + \beta_{pos} \qquad (7a)$$

$$\delta_{neg}(V) = \alpha_{neg}(V - V_L) \times \frac{\left((V_U - V_{neg}) + c_{neg}(V_{l\max} - V_{lmean})\right)}{\left((V_U - V_L) + c_{neg}(V_{l\max} - V_{l\min}) + l_{neg}\right)} + \beta_{neg} \quad (7b)$$

where V represents an element of the brightness of the input image; $V_{gmean}$ represents the average of an element of the brightness of the entire image; $V_{lmax}$, $V_{lmin}$, and $V_{lmean}$ represent the maximum, minimum, and median values in a local area; and $\alpha_{(pos \,\&\, neg)}$, $\beta_{(pos \,\&\, neg)}$, and $l_{(pos \,\&\, neg)}$ represent discretionary variables which are used for adjusting each parameter.

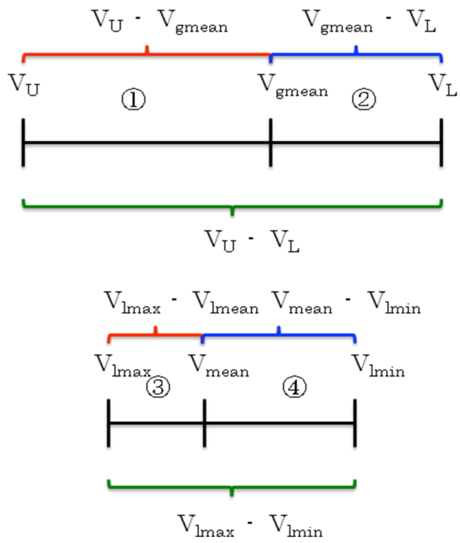



**Figure 5:** Parametric relationship of input

The idea behind Eqs. 7a and 7b is based on the following reasoning: The upper part of Fig. 5 shows the parametric relationship of the entire image. The input image becomes brighter as the width of ② grows, and element ② is positive. The formula for the percentage of the positive element is $(V_{gmean} - V_L) / (V_U - V_L)$. The lower part of Fig. 5 shows the local parametric relationship of the image. As mentioned earlier, the input image becomes brighter locally as the width of ④ grows, and element ④ is positive. The formula for the percentage of the positive element is $(V_{lmean} - V_{lmin}) / (V_{lmax} - V_{lmin})$. Eq. 7a is calculated by combining and correcting the entire image and the local elements. Negative elements can be similarly created.

### 3.3. Color contrast model based on S-curve conversion

If the reverse S-curve conversion is similarly applied to the color contrast, the clarity of the image is lost, as the color is compressed relative to the achromatic image while the dynamic range of the area where the color is heavily biased expands [6]. Instead, we used a logistic function for the color sense model of the cones to develop a color contrast model. The logistic function is a differential equation that explains population growth in population biology. The proposed method uses it to express a process to enhance the chromatic contrast of each cone:

$$L(C_{R-G}) = \frac{\max\left(|C_{R-GU}|, |C_{R-GL}|\right) \times 2}{1 + e^{-a\left(C_{R-G} + b\left((C_{R-Glmean} - C_{R-Gldev}) - (C_{R-Ggmean} - C_{R-Ggdev})\right)\right)}} - \max\left(|C_{R-GU}|, |C_{R-GL}|\right) \quad (8)$$

$$L(C_{Y-B}) = \frac{\max\left(\left|C_{Y-BU}\right|, \left|C_{Y-BL}\right|\right) \times 2}{1 + e^{-a\left(C_{Y-B} + b\left(\left(C_{Y-Blmean} - C_{Y-Bldev}\right) - \left(C_{Y-Bgmean} - C_{Y-Bgdev}\right)\right)\right)}} - \max\left(\left|C_{Y-BU}\right|, \left|C_{Y-BL}\right|\right) \quad (9)$$

where $C_{R\text{-}Glmean}$ and $C_{Y\text{-}Blmean}$ represent the average of $C_{R\text{-}G}$ and $C_{Y\text{-}B}$ in a local area; $C_{R\text{-}Ggmean}$ and $C_{Y\text{-}Bgmean}$ represent the average of $C_{R\text{-}G}$ and $C_{Y\text{-}B}$ in the entire image; $C_{R\text{-}Gldev}$ and $C_{Y\text{-}Bldev}$ represent the deviation of $C_{R\text{-}G}$ and $C_{Y\text{-}B}$ in a local area; $C_{R\text{-}Ggdev}$ and $C_{Y\text{-}Bgdev}$ represent the deviation of $C_{R\text{-}G}$ and $C_{Y\text{-}B}$ in the entire image; and a and b are discretionary constants which are used to adjust the color intensity.

The logistic functions in Eqs. (8) and (9) move to the right or left depending on the input image. The move in Eq. (8) is:

$$b((C_{R-Glmean} - C_{R-Gldev}) - (C_{R-Ggmean} - C_{R-Ggdev}))$$

This calculates the difference between elements of a local area and elements of the entire image. Thus, to enhance the color of the local area, changes in a local area in the input image are converted into the distance of the move.

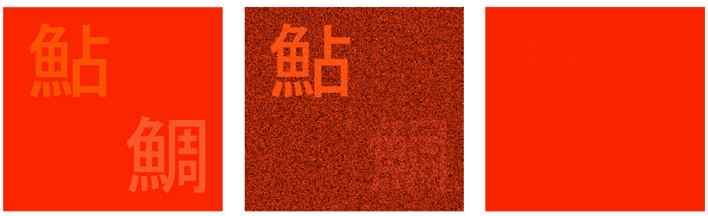
## 4. EVALUATION EXPERIMENT

To evaluate our method for correcting images, we evaluated visibility and image impressions. We also evaluated whether the method improved images for people with defects in color vision.

We recruited 14 university students – 11 men and 3 women. Three of them were engaged in image processing research.

### 4.1. Evaluation of visibility

On a scale of 1 (no recognition, or impression not retained) to 7 (easily recognizable, or impression maintained), subjects assessed the original and corrected images (corrected by both the proposed model and by histogram equalization in LabSpace software) to see whether the characters in the images were easy to recognize and the image impressions in the original images were maintained in the corrected images. Items for evaluation were selected on the basis that radical changes in the characteristics of images, while making the contents easier to see, might radically change the impressions of the images.




(a) Original image (b) Equalization (c) Proposed method

**Figure 6:** Example of experimental images

Subjects evaluated the images in Fig. 6 (4 colors [R, G, B, Y] × 6 = 24 images in total). The Lab color space was used for the histogram equalization because the RGB color space does not consider the visual characteristics of humans: the Lab color space is designed to simulate the logarithmic sensitivity of eyes; it expresses colors non-linearly by dividing them into brightness and color differences. For these reasons, we believe that the comparison with the proposed method is appropriate.

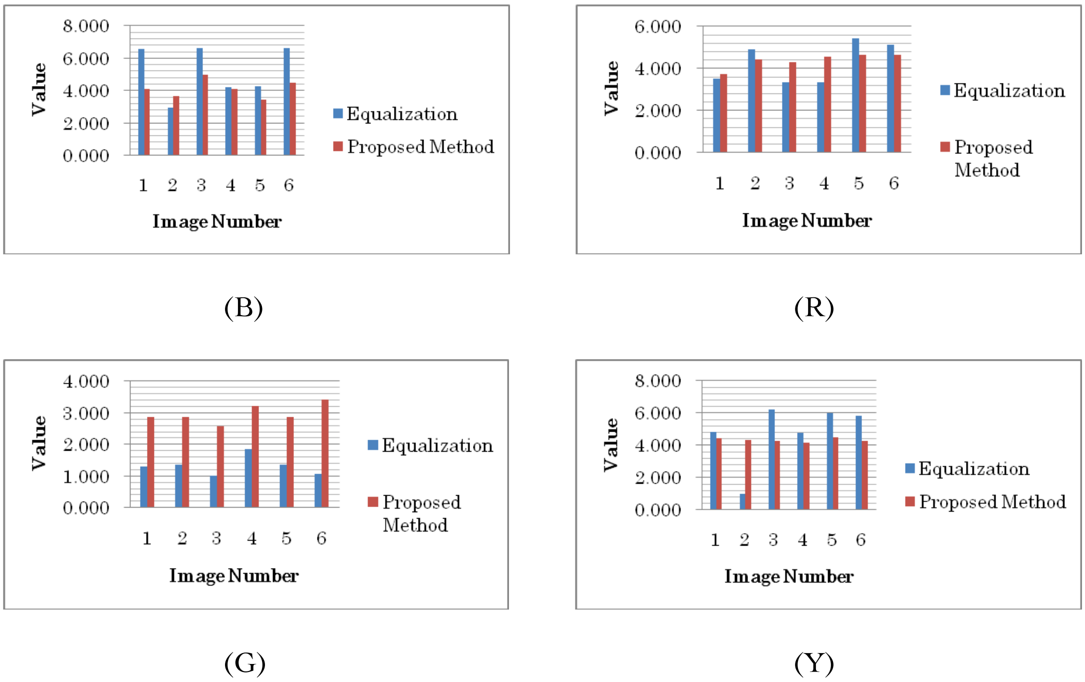
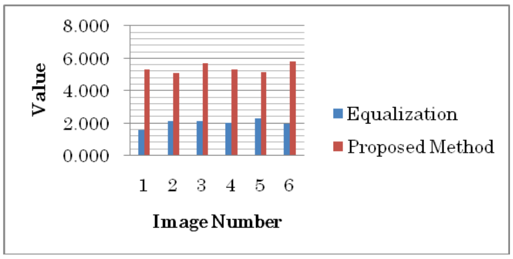


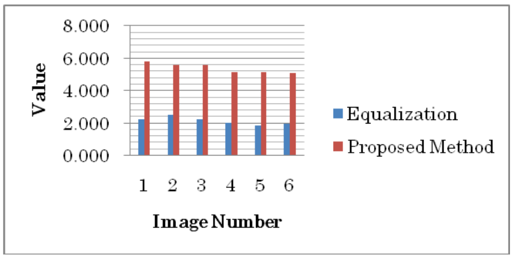

**Figure 7:** Results of visibility evaluation

**Table 1:** Results of questionnaire on visibility

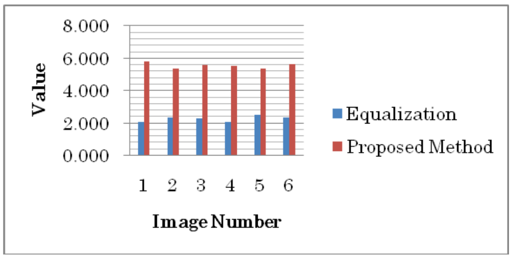
| | B1 | B2 | B3 | B4 | B5 | B6 | Average |
|---|---|---|---|---|---|---|---|
| Equalization | 6.571 | 2.929 | 6.643 | 4.214 | 4.286 | 6.643 | 5.214 |
| Proposed Method | 4.071 | 3.643 | 5.000 | 4.071 | 3.429 | 4.500 | 4.119 |
| | R1 | R2 | R3 | R4 | R5 | R6 | Average |
| Equalization | 3.500 | 4.929 | 3.357 | 3.357 | 5.429 | 5.143 | 4.286 |
| Proposed Method | 3.714 | 4.429 | 4.286 | 4.571 | 4.643 | 4.643 | 4.381 |
| | G1 | G2 | G3 | G4 | G5 | G6 | Average |
| Equalization | 1.286 | 1.357 | 1.000 | 1.857 | 1.357 | 1.071 | 1.321 |
| Proposed Method | 2.857 | 2.857 | 2.571 | 3.214 | 2.857 | 3.429 | 2.964 |
| | Y1 | Y2 | Y3 | Y4 | Y5 | Y6 | Average |
| Equalization | 4.857 | 1.000 | 6.214 | 4.786 | 6.000 | 5.857 | 4.786 |
| Proposed Method | 4.429 | 4.357 | 4.286 | 4.143 | 4.500 | 4.286 | 4.333 |



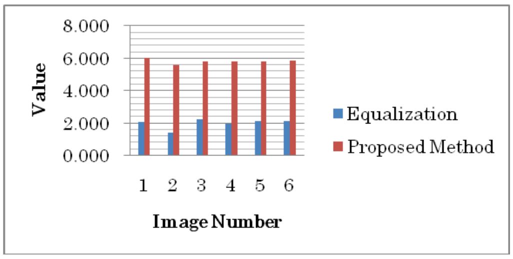

(B)




(R)




(G)




(Y)

**Figure 8:** Results of impression evaluation result in visibility

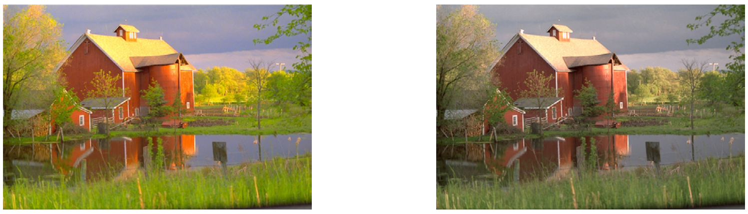
**Table 2:** Results of questionnaire on image impression evaluation in visibility experiment

| | B1 | B2 | B3 | B4 | B5 | B6 | Average |
|---|---|---|---|---|---|---|---|
| **Equalization** | 1.571 | 2.143 | 2.143 | 2.000 | 2.286 | 1.929 | 2.012 |
| **Proposed Method** | 5.286 | 5.071 | 5.714 | 5.286 | 5.143 | 5.786 | 5.381 |
| | **G1** | **G2** | **G3** | **G4** | **G5** | **G6** | **Average** |
| **Equalization** | 2.214 | 2.500 | 2.214 | 2.000 | 1.857 | 1.929 | 2.119 |
| **Proposed Method** | 5.786 | 5.571 | 5.571 | 5.143 | 5.143 | 5.071 | 5.381 |
| | **R1** | **R2** | **R3** | **R4** | **R5** | **R6** | **Average** |
| **Equalization** | 2.071 | 2.357 | 2.286 | 2.071 | 2.500 | 2.357 | 2.274 |
| **Proposed Method** | 5.786 | 5.357 | 5.571 | 5.500 | 5.357 | 5.643 | 5.536 |
| | **Y1** | **Y2** | **Y3** | **Y4** | **Y5** | **Y6** | **Average** |
| **Equalization** | 2.071 | 1.429 | 2.214 | 1.929 | 2.143 | 2.143 | 1.988 |
| **Proposed Method** | 6.000 | 5.571 | 5.786 | 5.786 | 5.786 | 5.857 | 5.798 |

#### 4.1.1. Result of visibility evaluation

Table 1 and Fig. 7 show the subjects' results on visibility. Table 2 and Fig. 8 show their results on impressions. In the evaluation of visibility, the results of B and Y show that the histogram equalization was evaluated higher than the proposed method, while those of R and G show that the proposed method was evaluated higher. But the average of the R, G, B, and Y results shows almost no difference between the histogram equalization method (3.90) and the proposed method (3.94) (Wilcoxon's signed-rank test, T = 96). When 4 images in which no difference was found were omitted, there was still no difference between the 2 methods ($T_{0.05}$ = 52). Therefore, the proposed method has a processing capacity similar to that of histogram equalization.

The results of the impressions show that the proposed method was evaluated higher in all colors and images. The average of the R, G, B, and Y results was 2.10 by histogram equalization versus 5.52 by the proposed method (Wilcoxon test, T = 0). So the proposed method maintains the impressions better, as T0.05 = 81. Result of visibility evaluation



(a) Original image (b) Image processed by proposed method

**Figure 9:** Example of experimental image

### 4.2. Evaluation of image impressions

Subjects evaluated image impressions on a scale of 1 (worse) through 4 (no change) to 7 (better), taking into account changes in clarity and ease of viewing, by comparing 30 original images (of persons, animals, landscapes, and buildings) with the images corrected by the proposed method (Fig. 9). A poorer image was radically different in its distribution of information on brightness and color differences, and the impression of the original was not maintained. The results show that the images output by the proposed method received higher evaluations (>4) than the original images, indicating that the proposed method can improve clarity and ease of viewing while maintaining impressions.

#### 4.2.1. Results of image impression evaluation

Figure 10 shows the average evaluations by the 14 subjects. Students rated 29 images as clearer and 27 images as easier to view (24 overall). The average evaluation value of the clarity of the 30 images was 5.25 (Wilcoxon test, T = 19). When 2 images with no difference were omitted, the significance was higher (T0.05 = 116). This confirms that the images were corrected appropriately to improve clarity.

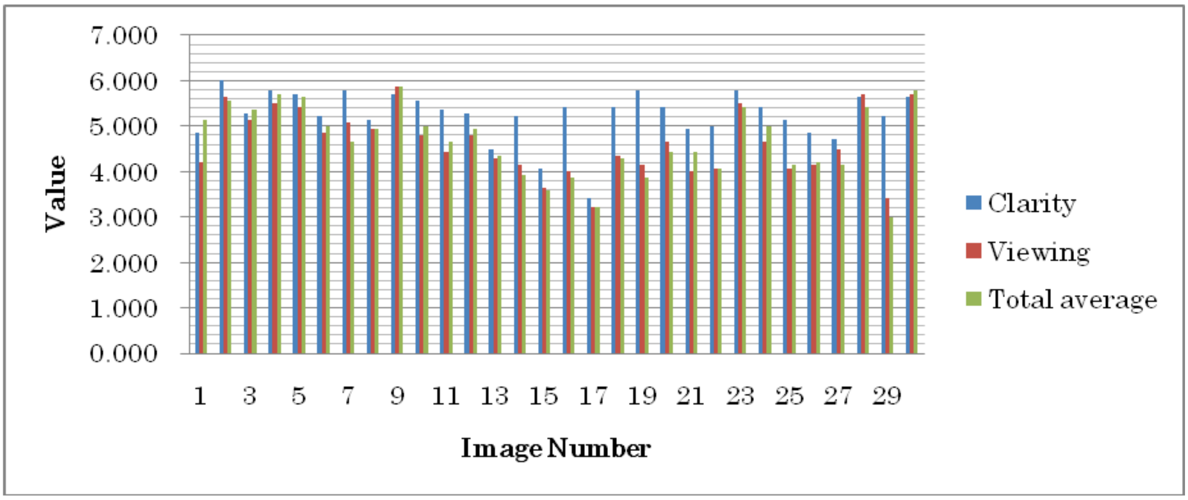



**Figure 10:** Results of questionnaire on image

The average evaluation value of the ease of viewing of the 30 images was 4.65 (Wilcoxon test, T = 13). When 12 images with no difference were omitted, the significance was higher

(T0.05 = 40). This confirms that the images were corrected appropriately to improve the ease of viewing.

Overall, the average evaluation value of the 30 images was 4.65 (Wilcoxon test, T = 14). When 13 images with no difference were omitted, the difference was significant (T0.05 = 34). This confirms that the images were appropriately corrected.

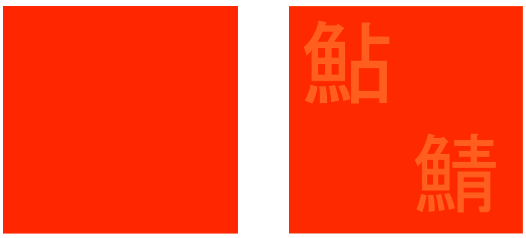
### 4.3. Test of subjects with defects in color vision

We assumed that when colors are hard to discern, we can make edges clearer by enhancing differences in brightness, making it easier for viewers with defects in color vision to discern color boundaries. We also assumed that we can assess the effectiveness of this approach by verifying increases in outline information. So we assessed whether images would become easier to perceive by people with different color perceptions and color identification characteristics from the majority of people.

We applied edge enhancement filters to both the original and processed images [5] and retrieved a luminance histogram from each.

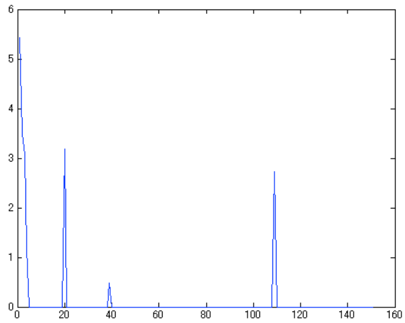
#### 4.3.1. Evaluation results

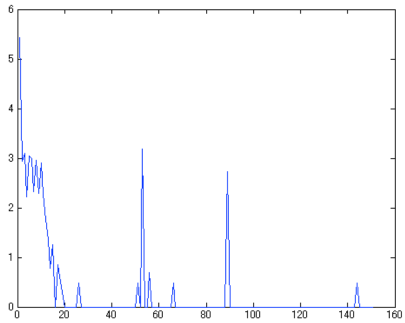
Figure 11b shows the image output by the proposed method from the image in Fig. 11a. Fig. 12 shows the histograms retrieved after edge enhancement. The histogram distribution of the processed image was wider and the edge elements increased. As seen in 4.1.1, the impressions of the original images were maintained, indicating that the correction maintained the characteristics of the original images for people with defects in color vision.




(a) Original image (b)Image output by proposed method

**Figure 11:** Image corrected by proposed method




(a) Histogram of Fig. 11 (a) image with edge

(b) Histogram of Fig. 11 (b) image with edge

**Figure 12:** Histogram evaluation

## 5. DISCUSSION

The result described in 4.1.1 indicates that the proposed method can improve image visibility as well as histogram equalization can, while keeping the impressions of the original images unchanged. However, it was evaluated poorer in B and Y. To improve the visibility in B and Y, the $\delta_{neg}$ value in Eq. (6) could be increased when elements deviate excessively from the average in the brightness distribution of the entire image. However, this would unnaturally alter the brightness in natural images. Instead, we designed a way to maintain the impressions by slightly reducing the visibility.

The result described in 4.2.1 indicates that the proposed method can improve the clarity and ease of viewing. Image processing software is generally not good at processing images in accordance with their local characteristics, and instead processes them uniformly. In doing so, they radically alter the entire impression of the images, sometimes for the worse (e.g. Fig. 6b). Our proposed method reduces this problem by processing images according to the local brightness and color elements. In this sense, it can correct images appropriately. However, some of the results show that the images were altered for the worse. This is probably because those images did not have much variety in color, and the proposed method altered the entirety of the images radically. To improve such weakness, it is necessary to further analyze the color distribution of images in their entirety and modify parameters in such a way that the S-curve becomes straight when specific color elements occupy most of the images.

In 4.3, we tested the effectiveness of the proposed method at improving images for people with defects in color vision. We used an image of a kanji character, but in the future we plan to use natural images. However, we believe that it will be difficult to improve the visibility of images for people with defects in color vision simply by changing colors, because there are many types of defects and it is difficult to improve visibility for all of them. We plan to perform further research to improve the correction of brightness elements in order to improve visibility while maintaining impressions.

## 6. CONCLUSION

We devised a method of correcting images to make them easier to see while keeping the impressions of the original images unchanged, by developing a mathematical model of the visual characteristics of humans. The method improves visibility as well as an existing method does while keeping the impressions of the original images unchanged. Unlike general image processing software, which corrects the brightness and colors of images uniformly, the proposed method corrects them by taking into consideration both overall and local characteristics of images. It can also improve the visibility of images for people with defects in color vision while keeping the impressions of the original images unchanged.

We plan to improve the mathematical model of the visual characteristics of colors, because we did not verify our assumption based on the S-curve. We plan to do so.

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